



Full length article



## GPS-based activity space exposure to greenness and walkability is associated with increased accelerometer-based physical activity

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### A B S T R A C T

**Introduction:** Built and natural environments may provide opportunities for physical activity. However, studies are limited by primarily using residential addresses to define exposure and self-report to measure physical activity. We quantified associations between global positioning systems (GPS)-based activity space measures of environmental exposure and accelerometer-based physical activity.

**Methods:** Using a nationwide sample of working female adults (N = 354), we obtained seven days of GPS and accelerometry data. We created Daily Path Area activity spaces using GPS data and linked these activity spaces to spatial datasets on walkability (EPA Smart Location Database at the Census block group level) and greenness (satellite vegetation at 250 m resolution). We utilized generalized additive models to examine nonlinear associations between activity space exposures and accelerometer-derived physical activity outcomes adjusted for demographic characteristics, socioeconomic factors, and self-rated health.

**Results:** Higher activity space walkability was associated with higher levels of moderate-vigorous physical activity, and higher activity space greenness was associated with greater numbers of steps per week. No strong relationships were observed for sedentary behavior or light physical activity. Highest levels of moderate-vigorous physical activity were observed for participants with both high walkability and high greenness in their activity spaces.

**Conclusion:** This study contributes evidence that higher levels of physical activity occur in environments with more dense, diverse, and well-connected built environments, and with higher amounts of vegetation. These data suggest that urban planners, landscape architects, and policy makers should implement and evaluate environmental interventions to encourage higher levels of physical activity.

### 1. Introduction

Physical inactivity is a major behavioral risk factor for cancer, cardiovascular disease, diabetes, hypertension, and other chronic diseases (Sallis et al., 2016), yet only 53% of US men and 47% of US women reach physical activity guidelines (Ward et al., 2008). Research, informed by the ecosocial model (Krieger, 2005), has highlighted the potential role of environmental contextual factors to provide opportunities for physical activity (Zhang et al., 2016; McNeill et al., 2006; James et al., 2015; Sallis et al., 2012).

Two features that have emerged as potential facilitators of physical activity are the built and natural environment. The built environment,

provides opportunities or barriers to routinely walk and be physically active (Handy et al., 2002; Cdc, 2011). Characteristics of the built environment such as population density, land use mix, connectivity and design have been repeatedly found associated with higher accessibility levels (Leslie et al., 2007; Frank et al., 2010), being able to walk to a higher number of daily destinations and thus with higher population levels of physical activity (Feng et al., 2010). Walkability measures are commonly used to encompass these built environment features and have been linked to transport-related physical activity (Hirsch et al., 2014; Hirsch et al., 2014), particularly utilitarian walking (Cerin et al., 2007). People living in environments with more destinations within walking distance walk more often (Villanueva et al., 2014; Norman et al., 2013;

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Marquet and Miralles-Guasch, 2015; Marquet and Miralles-Guasch, 2016) and for longer distances (Millward et al., 2013; Owen et al., 2007). Within the natural environment, exposure to high levels of vegetation and green space has also been associated with increased physical activity (James et al., 2015; Almanza et al., 2012; Lachowycz et al., 2012; Vich et al., 2021). Studies have found that exercise facilities such as fitness areas or children play areas within green spaces, together with enjoyable scenery and seeing other active people, may encourage physical activity (Potwarka et al., 2008; Kerr et al., 2012; Mitra et al., 2015; Wendel-Vos et al., 2007; McMorris et al., 2015; Dewulf et al., 2016; Cohen et al., 2012; DelCampo et al., 2017; Marquet et al., 2019a,2019b). Green spaces may also encourage leisure- and transportation-related physical activity, as green spaces provide both a walking/cycling destination and venue for play and exercise (Bedimo-Rung et al., 2005) although findings are inconsistent (Schipperijn et al., 2013; Ord et al., 2013).

In the past two decades, studies have incorporated device-based methods to assess physical activity (e.g. pedometers, accelerometers, other biosensors) (Hajna et al., 2015). These tools offer high-resolution, accurate measurements of movement (Troiano et al., 2014). Use of accelerometry data is starting to provide new evidence on the association between walkability and physical activity worldwide (Sallis et al., 2016; Vanhelst et al., 2013), in dense urban spaces (Rundle et al., 2016), among particular demographic groups (King et al., 2011; Hirsch et al., 2016; Rodríguez et al., 2012), and across several domains (Yang et al., 2014; Marquet and Hipp, 2019; March(7):20–26.; Marquet et al., 2020). Use of device-based measures is also advancing in green space studies (James et al., 2015; Halonen et al., 2020), where accelerometers have extended evidence linking greenness with increased physical activity among children (Almanza et al., 2012; Lachowycz et al., 2012; Ward et al., 2016) and adults (Dewulf et al., 2016). However, research has struggled with small sample sizes and mixed findings.

Studies trying to assess environmental exposures have relied on administrative boundaries (Leal and Chaix, 2011; Foster and Hipp, 2011), which may introduce significant measurement error by assuming participants stay within these boundaries (Spielman and Yoo, 2009) and introducing well-documented spatial bias such as the NEAP (Kwan, 2018) or UGCop (Kwan, 2018). In the past, many studies have centered measurements around a participant's residential address (Sarmiento et al., 2010; van Loon et al., 2014; Hwang et al., 2016), failing to acknowledge spaces participants encounter throughout their daily lives (Hirsch et al., 2016,2014; Vich et al., 2017), and making important assumptions about size and shape of areas around an address to consider (James et al., 2014). Overall, these traditional geographic measures of neighborhood have failed to accurately capture environmental exposures which has led some to suggest that the literature needs to move beyond notions of contextual influence that rely on using such specific fixed locations (Kwan, 2018; Sheller and Urry, 2006). GPS technology can overcome some of these limitations by offering a dynamic measure of the environmental context (Jankowska et al., 2014). GPS-based measures can generate "activity spaces" that represent the area within which people move or travel in the course of their daily activities. GPS-based activity spaces include all movements during the day for all purposes and with any mode of transport (Hirsch et al., 2014); (Marwa et al., 2021), and they can later be paired with GIS data to measure environmental exposures (Ward et al., 2016; Chaix et al., 2013; Kerr et al., 2012). Recently, researchers have used the triad of GPS location, GIS exposure, and sensor-based physical activity outcomes to create a transdisciplinary field coined as "Spatial Energetics (Marquet et al., 2020; James et al., 2016). Linking behavioral and spatial data facilitates the examination of location and physical activity at precise spatiotemporal scales (James et al., 2016). While this nascent work shows promise, additional research is needed using larger samples and examining greenspace. There also exists a gap for examining nonlinear relationships, which could potentially account for changes in physical activity that might occur once certain thresholds or minimum values of

environmental features are present (Moudon et al., 2006; Sugiyama et al., 2012). Similarly, limited environmental variability may impact measured associations between the environment and physical activity.

This study fills a gap in the literature by examining device-based measured physical activity with GPS-based activity space measures of greenness and walkability. With participants located throughout four different study sites across the US, we also maximized exposure variability and context. We hypothesized that higher levels of greenness and walkability within a participant's activity space would be associated with higher intensities of physical activity.

## 2. Methods

### 2.1. Population

A sample of female participants was recruited from four sites from the National Cancer Institute (NCI)-funded Transdisciplinary Research in Energetics and Cancer (TREC) initiative (Patterson et al., 2013). As described elsewhere (James et al., 2017), the sample was made up of working adults (University of California, San Diego (UCSD) and Washington University in St. Louis (WUSTL)), members of the prospective Nurses' Health Study II cohort (Harvard University (Harvard)), and breast cancer survivors (University of Pennsylvania (UPenn)). Eligibility criteria for this study were: female, 21–75 years old, self-reported BMI 21.0–39.9, ability to ambulate unassisted, not pregnant or breastfeeding, and willing to wear monitoring devices for seven days. Site-specific eligibility criteria included: currently employed full or part-time (WUSTL) and previously diagnosed with breast cancer (UPenn). Furthermore, 17% of the UCSD sample was comprised of confirmed breast cancer survivors. The Harvard sample was selected from participants in the Nurses Health Study II with a BMI less than 40, and was sampled to evenly represent varying population densities and all Census regions of the US (African Americans were oversampled). For the Harvard sample, 120 recruitment letters were sent out and 91 participants provided data for this analysis. Institutional review boards at each university approved the protocol, and all participants provided informed consent.

Participants were enrolled over 12 months in 2012–2013, completed baseline surveys, and were instructed to wear an Actigraph GT3X+ accelerometer and a Qstarz BT1000X GPS device on the hip during all waking hours (except when showering, bathing, or swimming) for seven consecutive days. Participants removed devices at night to charge the GPS device.

All data in these analyses were centrally pooled and uniformly processed at UCSD.

### 2.2. Accelerometer data

Accelerometer data were screened manually for wear time compliance. We collected raw accelerometer data at 30 Hertz and aggregated as counts in one-minute epochs. Wear time was assessed using the Choi algorithm in Actilife 6.11, which assesses 90 consecutive minutes of zero counts as non-wear allowing for up to two minutes of nonzero counts to remove artifactual movement (Choi et al., 2011). Data were manually screened by trained personnel to identify valid days. Data were excluded if there were fewer than five days of data with 600 min per day of wear time or fewer than four days with 3000 min of total accelerometer wear time (Troiano et al., 2008). Counts per minute (CPM) from the vertical axis of the accelerometer were used to derive steps and physical activity intensities. We employed the Troiano physical activity cutpoints for sedentary ( $\leq 99$  CPM), light (100–2019 CPM), and moderate or vigorous physical activity ( $\geq 2020$  CPM) (Troiano et al., 2008). We also used the report of total steps recorded by the accelerometer.

### 2.3. Global positioning systems data

Qstarz GPS devices logged location coordinates, distance, speed, elevation, and time. Qstarz validation studies have reported accuracy of 3 m, and all GPS devices were evaluated for this level of accuracy before deployment. We configured devices to record location and time data at 15 s intervals.

### 2.4. Activity spaces

We analyzed GPS location data, aggregated by participant, using Python 2.7.2 and ArcPy for ArcGIS 10.4. We examined Daily Path Areas (DPA) adapted from previous literature (Hirsch et al., 2014; Zenk et al., 2011; Starnes, 2012) by creating 200 m merged buffers for all of a participant's GPS data (see Fig. 1). DPA are considered as the best approach to analyze the cumulative exposure experienced through daily mobility at the street level (Hirsch et al., 2014; Vich et al., 2017). To assess optimal activity space calculation (Hirsch et al., 2016; Patterson and Farber, 2015), sensitivity analyses were performed using two additional activity space approaches (standard deviation ellipse (SDE) and minimum convex polygon (MCP)) (see Supplemental Fig. 1). SDE measure the directional distribution of a series of points and are usually used to observe the normal range of spatial motion for an individual (Zenk et al., 2011; Starnes, 2012; Sherman et al., 2005; Rainham et al., 2010; Newsome et al., 1998). MCP, sometimes referred to as “home ranges”, represents the smallest polygon that contains all GPS points, with the outermost points serving as vertices. Detailed methods for creating activity space measures have been published previously (Zenk et al., 2011; Sherman et al., 2005; Fan and Khattak, 2008). Because mean walkability and greenness values for participants across different activity space types were highly correlated (Spearman's  $\rho > 0.76$  for walkability  $\rho > 0.91$  for greenness), results are presented only for DPAs.

### 2.5. Spatial datasets and exposures

#### 2.5.1. Greenness

Normalized difference vegetation index (NDVI) values estimate vegetation, or greenness, in an area. Reflected sunlight from satellite-measured red and near-infrared bands of the light spectrum are converted to generate NDVI values with a range of  $-1.0$  to  $1.0$  (larger values indicating higher vegetation density) (Kriegler et al., 1968). We used Moderate-resolution Imaging Spectroradiometer (MODIS) data deployed on NASA's Terra satellite. Imagery from July 2012 approximated the greenness levels at the time of data collection (Carroll et al., 2004). Average NDVI values from 250 m resolution satellite data were calculated for each activity space. Fig. 1 shows a participant's activity space linked to greenness.

#### 2.5.2. Walkability

Average area-weighted walkability values were calculated for activity spaces by averaging the sum of walkability values that fall within the activity space areas. Each activity space was linked to a walkability index from the US Environmental Protection Agency (EPA) Smart Location Database (SLD). SLD provides nationwide geographic data on 90 attributes summarizing built environment characteristics at the Census Block Group level (Ramsey and Bell, 2014). The walkability index was compiled using: Gross population density (people/acre) on unprotected land; Street intersection density (weighted, with auto-oriented intersections eliminated); and Land Use Diversity (based on mix of retail, office, service, industrial, entertainment, education, healthcare, and public administration employment). We created Z-scores (mean of 0, standard deviation of 1) for each measure across all Block Groups in the US and summed these Z-scores to estimate a walkability index for each Census Block Group. Higher walkability index indicates a more walkable neighborhood. All spatial exposures were calculated and appended to activity spaces using ArcGIS v10.6.1 (Redlands, CA).

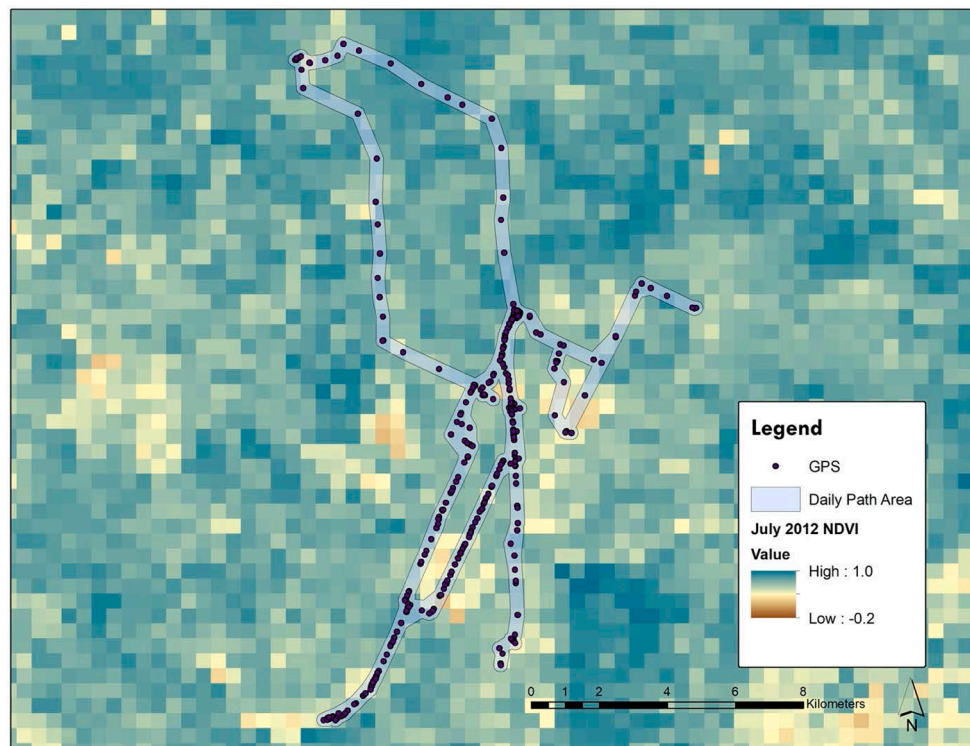


Fig. 1. Example of GPS data, daily path area activity spaces, and greenness.

### 2.5.3. Demographic characteristics

Survey data included information on age (years), race (White; Black; Other), marital status (Married; Never Married, Divorced, Separated, or Widowed), educational attainment (Less than College; College; Graduate Degree), household annual income from all sources (<\$50 K per year; \$50 K–\$69 K per year; \$70 K+ per year; Missing or Refused to Answer), employment status (Full Time; Part Time; Homemaker, Unemployed, Unable to Work; Retired), and self-rated health status (Poor, Fair, Good; Very Good, Excellent).

### 2.6. Statistical analysis

We used generalized additive models to estimate relationships between activity space walkability or greenness and weekly-averaged physical activity, adjusted for demographic characteristics. We built models including both greenness and walkability to assess potential confounding between environmental features. We also ran single-exposure models, but results were similar to mutually adjusted models (Supplemental Fig. 2) so we present mutually-adjusted models. We used natural splines to test for deviations from linearity and estimate thresholds. We compared Akaike's Information Criteria (AIC) values for linear versus nonlinear models. In addition, we explored interactions between greenness and walkability, to understand whether the relationship between greenness and physical activity differed according to levels of walkability, and vice versa. Data were analyzed in R (version 3.4.0).

## 3. Results

### 3.1. Population characteristics

Of the 354 participants, the majority were White (79%), married (71%), worked full time (51%), and made over \$70 K/year (46%) (Table 1). The average age of participants was 55.3 years. A minority of participants walked or biked to work (9%), and just over half rated their health as very good or excellent (54%). The majority of data was collected in the spring (36.4%) and winter (29.7%), while 24.7% of data were collected in the fall and 9.2% of data were collected in the summer months.

### 3.2. Main effects models

#### 3.2.1. Sedentary behavior

Fig. 2a and b show fully-adjusted spline models for sedentary behavior, mutually adjusted for both greenness and walkability within 200 m DPA activity spaces. There was no relationship between activity space greenness and sedentary behavior ( $p = 0.39$ ). There was a statistically significant ( $p = 0.047$ ) relationship between activity space walkability and sedentary behavior. Specifically, for walkability below 0 there was no relationship between walkability and sedentary behavior; however, from 0 to 1, higher levels of walkability were related to lower levels of sedentary behavior, and above 1, higher levels of walkability were associated with greater sedentary behavior.

#### 3.2.2. Light physical activity

The relationship between activity space greenness and light physical activity was positive and linear but did not reach statistical significance ( $p = 0.07$ , Fig. 2c and d). Alternatively, walkability was not associated with light physical activity.

#### 3.2.3. Moderate-vigorous physical activity

Models for both activity space measures demonstrated positive linear associations with accelerometer measured moderate-vigorous physical activity (MVPA) (Fig. 2e and f) although only walkability reached statistical significance. Greenness was positively associated with moderate-vigorous physical activity (a 0.1 increase in activity space NDVI was

**Table 1**

Characteristics of study population of working adults from four sites (UCSD, WUSTL, Nurses' Health Study II cohort (Harvard), and breast cancer survivors (UPenn)) who provided seven day samples of GPS and accelerometer data (N = 354).

	N	%
<i>Race</i>		
White	279	78.8
Black	58	16.4
Other	17	4.8
<i>Marital status</i>		
Never married, divorced/separated, widowed	103	29.1
Presently married or partnered cohabitation	251	70.9
<i>Educational attainment</i>		
Less than college	111	31.4
College	119	33.6
Graduate degree	124	35.0
<i>Household income</i>		
Less than \$50 k	79	22.3
\$50 k–\$69 k	54	15.3
Over \$70 k	163	46.1
Don't know or refused	58	16.4
<i>Employment status</i>		
Missing or refused	4	1.1
Full time	180	50.9
Part time	79	22.3
Homemaker, unemployed, unable to work	32	9.0
Retired	59	16.7
<i>Commute mode</i>		
All other modes	322	91.0
Walk or bike to work	32	9.0
<i>Health status</i>		
Poor, fair, good	163	46.1
Very good, excellent	191	54.0
<i>Study site</i>		
Harvard	91	25.7
Penn	116	32.8
UCSD	69	19.5
WUSTL	78	22.0

associated with a 0.8 (95% CI –0.6, 2.2) minute per day increase in moderate-vigorous physical activity), although this failed to reach statistical significance ( $p = 0.13$ ). A one-unit increase in walkability was associated with statistically significant 11.7 min/day (95% CI 1.8, 21.7) higher moderate-vigorous physical activity.

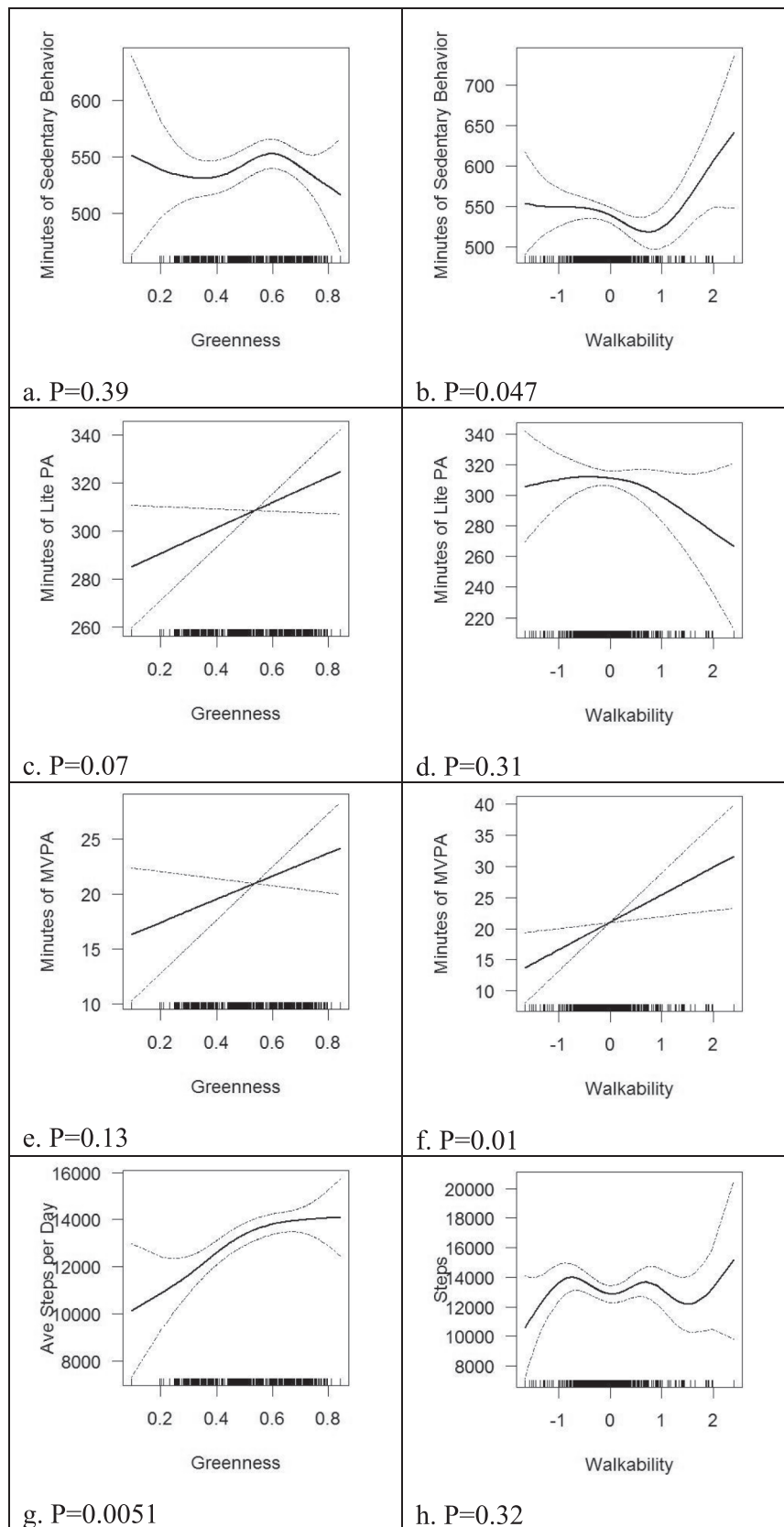
#### 3.2.4. Steps

Activity space greenness was positively associated with average number of steps per day in spline models ( $p = 0.0051$ ) (Fig. 2g). Association between greenness and steps was strongest for NDVI measures below 0.5 and attenuated somewhat at levels above 0.5. There was no relationship between activity space walkability and steps ( $p = 0.32$ ) (Fig. 2h).

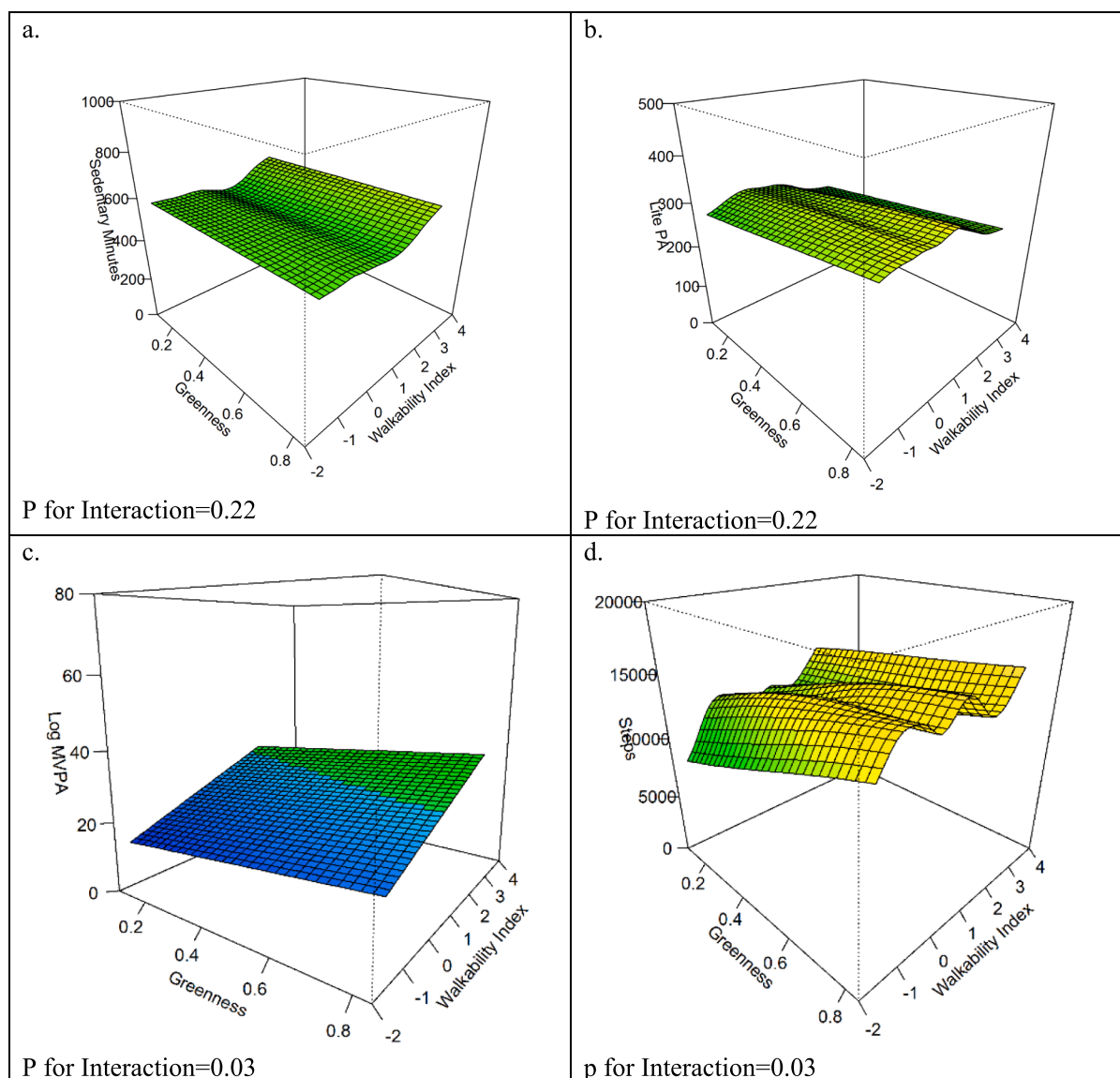
#### 3.2.5. Interactions between greenness and walkability

Analyses examining interactions between activity space greenness and walkability (Fig. 3a–d) revealed no evidence of interactions for sedentary behavior (Fig. 3a) or light physical activity (Fig. 3b). There was evidence of a linear interaction (Fig. 3c) ( $p = 0.03$ ) between greenness and walkability for moderate-vigorous physical activity, where levels of moderate-vigorous physical activity were highest among those who had activity spaces with both high walkability and high





**Fig. 2.** Fully-adjusted spline models for 200 m daily path area greenness and walkability and different measures of physical activity (PA) (sedentary behavior, light PA, moderate-vigorous PA, avg steps per day).



**Fig. 3.** Interactions between greenness and walkability for a. Sedentary minutes; b. Light physical activity; c. Moderate-vigorous physical activity; d. Steps.

greenness. There was also evidence of nonlinear interactions between greenness and walkability for steps (Fig. 3d) ( $p = 0.03$ ), where the highest step counts were observed for participants with activity spaces with the highest greenness and walkability; however, these relationships were not consistent across all levels of greenness and walkability.

#### 4. Discussion

Using data from a sample of women at four sites across the United States who provided a week of GPS and accelerometer data, we observed that participants whose activity spaces had higher levels of walkability also had higher levels of moderate-vigorous physical activity. Furthermore, higher activity-space greenness was associated with a greater number of steps per week. No strong relationships were observed for activity space exposures and sedentary behavior nor light physical activity. We found evidence of interactions between activity space greenness and walkability for moderate-vigorous physical activity, where the highest levels of moderate-vigorous physical activity were observed for participants who had activity spaces containing both high walkability and high greenness. Interactions between activity space greenness and walkability on the associations with steps were inconsistent.

Previous research has reported discordance between exposures measured at the residential and activity space-level (Chaix, 2018; Hurvitz and Moudon, 2012). These inconsistencies have prompted calls for increased examinations of relationships between non-residential environments and physical activity (Hirsch et al., 2014; Holliday et al., 2017). Shifting from a restrictive focus on residential environments to activity space measures allowed us to account for environmental exposures in the diverse places visited by participants (Chaix et al., 2017). Thus, we were able to include daily physical activity that takes place away from residential neighborhoods (Marquet et al., 2020; Hurvitz et al., 2014; Holliday et al., 2017; Kestens et al., 2018).

Our findings suggest that individuals may obtain higher levels of physical activity in walkable environments. While existent literature had already extensively explored this relationship at the neighborhood and residential scale (Hajna et al., 2015; Hwang et al., 2016; Sundquist et al., 2011; Lee et al., 2016; Hoehner et al., 2011; Kondo et al., 2009; Duncan et al., 2016), only a handful of articles has explored it at the activity space level (Chaix, 2018). Our results are consistent with Rundle's et al. (Rundle et al., 2016) which also used activity spaces and accelerometer-based measures of physical activity in New York City. This work showed a positive relationship between walkability and moderate physical activity. Using similar methods, Hirsch et al. (2016)

found consistent, although statistically non-significant, associations between density of destinations within participants activity spaces and physical activity in a group of community-dwelling older adults from Vancouver. Others have found that a change in walkability within an activity space can lead to increased physical activity (Andersen et al., 2017). Using self-reported measures of physical activity, Howell et al. (2017) found a positive and significant relationship between walkability and participants' transportation physical activity. These associations were stronger when walkability was measured at the activity space level, compared with only around the residential environment. Furthermore, the negative association between walkability and sedentary time in areas that reach a minimum threshold of walkability is consistent with theories advocating for minimum densities and compact development in order to generate physical activity or active transport (James et al., 2017; Christiansen et al., 2016; Cerin et al., 2017).

Our findings also suggest that higher greenness levels may be associated with daily steps or light physical activity. Among other studies using greenness at the activity space level, our results are consistent with Jansen et al. (2017), who studied natural environments and physical activity, and with Kang et al. (2017) who examined the association of recreational walking with the amount of land park/trails within activity spaces. They contrast, however, with the insignificant associations found by Zenk et al. (2011). Our positive association between greenness and average steps also contradicts van Heeswijck et al. (2015) who found a negative association between activity space-NDVI and walking for transport. Other studies exploring the association between either momentary or activity space exposure to greenness and physical activity outcomes have generally found a positive correlation (Almanza et al., 2012; James et al., 2017; Chaix et al., 2016). Inconsistencies may be partially explained by exclusion of walkability in combination with greenness. In that context, our results add important evidence that the interaction between greenness and walkability might be positively associated with moderate to vigorous physical activity and average number of steps (Shuvo et al., 2021). This is one of the first studies to jointly consider these effects, especially within activity spaces.

Our analyses were limited by the use of a sample of older women who were working adults, members of a prospective cohort of nurses, and breast cancer survivors, impacting generalizability, especially to men, who may interact differently with their environments. Second, GIS data on walkability and greenness may not capture all relevant environmental features (e.g., sidewalk availability, vegetation species, park amenities) that might promote activity. The use of NDVI as a proxy of the amount of accessible greenspace might be affected by the presence of large but inaccessible green areas. Additionally, different data sources (e.g. Landsat 8 or Sentinel-2) may provide higher spatial or spectral resolution that may lead to different results. Third, several data source features and processing decisions may have led to measurement error. Participants' activity during the one recorded week may not be representative of their complete routine behavior (Zenk et al., 2018). Similarly, our findings may suffer from selective daily mobility bias, or confounding by intrapersonal characteristics which arises when individual preferences simultaneously lead individuals to visit certain locations and also drive the behaviors conducted in those locations (Schipperijn et al., 2014; Carlson et al., 2015; Meseck et al., 2016). If this were true, the relationship we found would be overestimated; however, the degree to which this is true is unknown as we do not have detailed information from participants on why they visit specific locations.

Despite these limitations, our analyses contribute an understanding of the environmental characteristics of locations where individuals are active. Other substantial strengths include device-based, high spatio-temporal resolution GPS-based measures of activity spaces and accelerometer-based measures of physical activity in a relatively large sample. These measures were joined with high-quality data on greenness and walkability collected uniformly nationwide. While we were unable to characterize the urbanicity, history, or other contextual factors of the participant locations, the broad geographic sample and uniform

measurement of exposures increases generalizability across geographic contexts. Standardized approaches across multiple study sites enabled pooling of consistently collected data. We also explored nonlinear relationships, allowing us to explore potential threshold relationships. This is one of the first studies to examine activity spaces and physical activity using nonlinear approaches. Our observed evidence of interactions between walkability and greenness might be relevant for future analyses. Overall, this study adds evidence to the literature showing that higher levels of physical activity occur in environments that have higher walkability and amounts of vegetation. Along with other research, our findings might inform implementation and evaluation of interventions that increase neighborhood walkability and greenness. Our findings suggest that policies to increase density, diversity, and connectedness of the built environment may increase physical activity. In addition, this study indicates that interventions to plant vegetation should focus on doing so in areas where walkability is high to maximize opportunities for physical activity.

### CRediT authorship contribution statement

**Oriol Marquet:** Conceptualization, Data curation, Writing – original draft. **Jana A. Hirsch:** Conceptualization, Methodology, Formal analysis, Writing – original draft. **Jacqueline Kerr:** Writing – review & editing, Funding acquisition. **Marta M. Jankowska:** . **Jonathan Mitchell:** . **Jaime E. Hart:** . **Francine Laden:** . **J. Aaron Hipp:** Conceptualization, Writing – original draft, Project administration. **Peter James:** Conceptualization, Methodology, Formal analysis, Writing – original draft.

### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

### Acknowledgements

This work was supported by the NCI Centers for Transdisciplinary Research on Energetics and Cancer (TREC) (U01 CA116850, U54 CA155496, U54 CA155626, U54 CA155435, U54 CA155850) and NIH Grants (UM1 CA176726) and (R01 ES017017). This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 845570. Oriol Marquet is funded by a Ramón y Cajal fellowship (RYC-2020- 029441-I) awarded by the Spanish Ministry of Science and Innovation. Dr. James was supported by Harvard NHLBI Cardiovascular Epidemiology Training Grant T32 HL098048 and R01 HL150119, National Cancer Institute of the National Institutes of Health Award R00 CA201542, and NIDDK Grant P30 DK046200. Dr. Mitchell was supported by the National Cancer Institute of the National Institutes of Health Award F32 CA162847. Drs. Laden and Hart were supported by the National Institute of Environmental Health Sciences of the National Institutes of Health award P30 ES000002.

### Appendix A. Supplementary material

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.envint.2022.107317>.

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